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Discordant City Employment Cycles*

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Abstract

This paper estimates city-level employment cycles for 58 large U.S. cities and documents the substantial cross-city variation in the timing, lengths, and frequencies of their employment contractions. It also shows how the spread of city-level contractions associated with U.S. recessions has tended to follow recession-specific geographic patterns. In addition, cities within the same state or region have tended to have similar employment cycles. We find no evidence that similarities in employment cycles are related to similarities in industry mix, although cities with more-similar high school attainment, mean establishment size, and industrial diversity have tended to have more-similar employment cycles.

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1. Introduction

National business cycles have long been characterized as a sequence of alternating periods of recession and expansion. In the United States, for example, the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) is tasked with determining official recession and expansion turning points. The determination of official business-cycle turning points is fairly opaque and untimely, and the turning points themselves are the only output from the effort. To address these shortcomings, a large literature has developed applying various statistical techniques to determine turning points and to examine underlying business cycle parameters.[1]

The advantages of these statistical approaches relative to the NBER's committee approach are their replicability, transparency, and timeliness. Also, because of these advantages, statistical approaches are readily applicable to a wide variety of questions. For example, using the Markov-switching model of Hamilton (1989), the notion of distinct cyclical phases has been extended to subnational economies, revealing significant differences in the timing, length, and occurrence of state-level recessions (Owyang, Piger, and Wall, 2005). This research has also revealed that periods of national recession usually contain a spatial component in that a recession spreads across the country in a geographic pattern. The effects of the 1990-91 NBER recession, for example, were first felt in the Northeast and the Far West before spreading to interior states. The recession receded in reverse, ending relatively quickly for interior states and lasting well after the end of the official recession for coastal states.

[1] See Harding and Pagan (2008) and Chauvet and Hamilton (2006) for surveys and discussions.

This paper extends this line of research by documenting the substantial variation in the cyclical movement of city-level employment, with the aim of finding the determinants of spatial variations over the cycle. The specific question we address is whether the geographic patterns of city-level employment cycles are simply reflections of differences in city industrial compositions or whether spatial mechanisms are responsible. As cities are arguably more relevant geographic delineations of local economies than are states, our analysis should provide a more accurate picture of subnational business-cycles. As we show, city-level data also allow us to examine in greater detail the extent to which spatially similar economies have similar business-cycle experiences. This greater accuracy and detail provided by our city-level cycles will assist us in explaining the variation in subnational employment cycles and their associated geographic patterns.

In section 2 we determine the timing of the employment cycle phases for 58 large cities, which we describe relative to each other and to the national business cycle in section 3. In section 4 we estimate the relative importance of industrial and geographic factors in determining cyclical similarities between cities, and in section 5 we extend the analysis to include potential roles for human capital, channels of monetary policy, industrial diversity, and agglomeration. Section 6 concludes.

2. Estimating City Employment Cycles

For our purposes, a city is either a Metro Division or a Metropolitan Statistical Area that is not divided into Metro Divisions. We use current MSA definitions, which restricts our analysis to post-1990, and examine payroll employment for 1990.Q1-2008.Q1 for all 58 cities that had average employment above 500,000 over the period. To determine the employment-cycle phases of these cities, we apply the Hamilton (1989) Markov-switching model to each city's payroll employment series independently. The simplest version of this model has employment cycle phases arising from the economy switching periodically between two different underlying regimes, each with its own mean growth rate.[2] Let μ_0 be the mean growth rate when the economy is in expansion, and let μ_1, which is normalized to be negative, be the difference between the mean growth rates in expansion and contraction. Specify the growth rate of employment, y_t, as

$$y_t = \mu_0 + \mu_1 S_t + \varepsilon_t. \tag{1}$$

The switching in (1) is governed by the state variable, $S_t = \{0,1\}$. When S_t switches from 0 to 1, the growth rate switches from μ_0 to $\mu_0 + \mu_1$. Because $\mu_1 < 0$, S_t switches from 0 to 1 at times when the economy switches from expansion to contraction, or vice versa. Deviations from the mean growth rates are created by the stochastic disturbance, $\varepsilon_t \sim N(0,\sigma_\varepsilon^2)$.

In the Markov-switching model, the state variable, S_t, is unobserved, and arises from a first-order two-state Markov chain, so any persistence in the regime is completely summarized by the value of S_t in the previous period. More specifically, the probability process driving S_t is captured by the transition probabilities $\Pr[S_t = j \mid S_{t-1} = i] = p_{ij}$. We estimate the model using the multi-move Gibbs-sampling procedure for Bayesian estimation of Markov-switching models implemented by Kim and Nelson (1999).[3]

Simply put, the model estimates the growth rates of employment during contraction and expansion and determines for each period the probability that the economy is in contraction. To

[2] This follows Owyang, Piger, and Wall (2005 and 2008); Owyang, Piger, Wall, and Wheeler (2008); and Hamilton and Owyang (forthcoming). See Piger (2009) for a discussion of the basic Markov-switching model and extensions.
[3] See Owyang, Piger, and Wall (2005) for a detailed description of the estimation procedure.

obtain this probability, the model compares the actual growth rate to the two regimes' growth rates while also accounting for the persistence of the series. If employment growth switches periodically between rates close to those of the two regimes, the probability of contraction will tend to be either close to zero or close to one. For present purposes we are interested only in the timing of cities' employment-cycle phases—as captured by their probabilities of contraction—and seeing the extent to which they are related to industrial composition and spatial consideration. As such, our analysis is silent on how well the cities do within each phase. Previous research has found that expansion growth rates were related to human capital and industrial structure, but that contraction growth rates were related only to the prevalence of manufacturing employment (Owyang, Piger, Wall, and Wheeler; 2008).

The model in (1) could be augmented to include additional dynamics, such as linear autoregressive dynamics, which might improve the model's fit of the data. However, this simple shifting-mean model has been shown to accurately identify the timing of NBER business cycle phases when applied to aggregate U.S. output and employment data, despite being statistically rejected in favor of more complicated models.[4] As our goal is limited to dating business cycle regime shifts between high and low growth phases, we restrict our attention to the simple shifting-mean model to identify the dates of these shifts. More highly parameterized models could be useful if our goal were instead to determine whether the data generating process for the city-level data was linear or nonlinear, an interesting question that we do not address here.

Before applying the model to our cities, we estimate the probability of employment contraction for the United States and compare it with the official NBER recession dates. Our results are illustrated by Figure 1 in which NBER recessions are indicated by the shaded areas. As is well-known, employment growth languished long after the 1990-91 and 2001 NBER

[4] See, e.g., Albert and Chib (1993) and Chauvet and Piger (2003).

recessions had ended, which shows up here as the probability of employment contraction remaining high beyond the ends of NBER recessions. The figure also shows a less-well-known result: U.S. employment contractions began prior to official recessions for each of the last three recessions. Specifically, the 1990-91 recession was surrounded by an employment contraction that ran from 1990.Q2 to 1992.Q2, two quarters before the official recession began until five quarters after it ended. The 2000 recession was surrounded by an employment contraction that began in 2000.Q4, two quarters prior to the recession, and ended in 2003.Q3, seven quarters after the recession had ended. Finally, the U.S. was experiencing an employment contraction two quarters prior to the start of the most recent NBER recession in 2008.Q1.

The model performs well for the cities in our sample, making the determination of contractionary periods fairly straightforward. Figure 2 shows the estimated contraction probabilities for the six largest cities in our sample. The first thing to note is the tendency for the contraction probabilities to be close to either one or zero, allowing for a clear separation of the employment series into contraction and expansion regimes. Also note the differences across cities: Although the cities' contractions tended to have occurred around the same general time periods, there were significant differences in their starting and ending dates, and, therefore, their lengths. For example, Los Angeles remained in contraction for much longer than the other four cities during the early 1990s, and Houston and Atlanta experienced the longest contractions of the early 2000s. Also notice that, by 2008.Q1, only three of the cities were in contraction, even though the national contraction had already begun. Three of these cities also exhibited some idiosyncratic switching: Los Angeles experienced a double-dip contraction during 2001-2003, Houston experienced a brief contraction in 1998-1999, and Washington's employment remained in its expansion phase throughout the early 2000s.

Figure 3 illustrates the estimated contraction probabilities for the six smallest cities in our sample. Because smaller economies tend to have noisier data, the separation into two business cycle regimes is not always as clean as for the largest cities. Even so, the model does identify several contraction episodes for each city, many of which coincide with contractions for the national economy. Idiosyncratic switches were also common: Bethesda, Hartford, Buffalo, and Rochester experienced contractions in the mid-1990s; Buffalo and Rochester experienced contractions in the mid 2000s; and Bethesda and Providence were in contraction by 2006.

Figures 2 and 3 also illustrate a number of relationships that we consider in subsequent sections. For example, even though Bethesda and Washington are in the same MSA, their employment cycles are very different.[5] This is reminiscent of Voith (1998) and Chang and Coulson (2001), who consider whether city centers and their suburbs might have their own, but perhaps related, agglomeration processes. Notice also the similarity between the employment cycles of Buffalo and Rochester, two neighboring cities in the same state, and the different cycles of Providence and Hartford, two relatively close cities in different states.

Our results for all 58 cities are summarized in Table 1, which indicates for each quarter whether a city is in contraction or expansion.[6] For illustrative purposes the table is shaded for periods for which U.S. employment was in contraction. The main features of Figures 2 and 3 discussed above also appear in Table 1: Although cities tended to have experienced contractions around the same times as each other, the starting and ending dates of these contractions differed a great deal; idiosyncratic contractions occurred for a number of cities during the mid 1990s and mid 2000s; and a significant number of cities were not in contraction yet by 2008.Q1. Finally, it was not uncommon for cities to completely miss the contractions felt elsewhere: five of the cities

[5] See Wall (2012) for an analysis of the links between the employment cycles of neighboring cities.
[6] To achieve this binary identification, we adopt the convention that a contractionary quarter is one for which the probability of contraction is greater than 0.5.

did not experience a contraction during the early 1990s, seven did not experience a contraction in the early 2000s, and Virginia Beach didn't experience a contraction during either period.

Figure 4 illustrates the differences across cities in the frequency of contraction over the period.[7] The figure shows that city-level contraction frequencies varied a great deal around that of the U.S., which was in an employment contraction 27 percent of the time. According to our results, 12 cities were in contraction between 42 and 69 percent of the time, whereas 15 cities were in contraction less than 21 percent of the time. All five cities in Ohio and Michigan were among the high-frequency group, along with three of the eight cities in California. The low-frequency cities were more evenly distributed, although proximity to high-contraction-frequency cities was no barrier to membership in this group. For example, Indianapolis and Louisville were in contraction relatively infrequently, despite their proximity to the high-frequency cities in Ohio and Michigan.

3. Aggregated and Geographic Patterns of City Contractions

The city-level experiences outlined above can be reaggregated to illustrate their relationship with country-level recessions and employment contractions. In Figure 5, which tracks the number of cities in contraction over time, U.S. contractions occurred soon after the number of cities in contraction began to climb, and ended soon after the number began to fall.[8] At no time, however, were all 58 cities in contraction. For one, as pointed out above, during each U.S. contractionary period, several cities remained in expansion throughout. For another, some cities will have already exited their contraction before other cities had entered theirs. In

[7] The numbers underlying the figure are in the first column of Appendix 1.
[8] One could make this figure more complicated by applying employment shares to obtain a weighted sum of city contractions, but because, as we show below, city size is unrelated to the occurrence of contractions this only changes the scale of the figure without affecting the story.

fact, it is misleading to even call U.S. contractions “national” in that large geographic components of the nation do not experience them at the same time, if at all. The U.S. contraction and expansion switches reflect a rolling weighted aggregate of the local-level switches. It is more accurate, therefore, to say that aggregate U.S. contractions occur when enough local economies have entered into contraction to make nationally aggregated data switch into its contraction phase. The shock that results in local and, eventually, aggregate contractions might be experienced nationwide, but the whole nation need not enter into contraction for an aggregate contraction to occur. Nor, as we have seen, does there need to be an aggregate contraction for local economies to switch into contraction.

As illustrated by Owyang, Piger, and Wall (2005), state contractions tend to follow geographic patterns. They show, for example, that in the period surrounding the 1990-91 NBER contraction, states on the east coast switched into contraction first, followed by states on the west coast, and the swathe of states between Texas and Montana missed out on the contraction entirely. As the state contractions ebbed during 1991, they receded back to the coastal states and lingered on for sometimes years longer. Although much of this pattern is evident in our city-level results, our data start in 1990 so we cannot see the pattern by which the early-switchers went into contraction. Even so, the official recession did not begin until 1990.Q4, yet many cities were in contraction at least two quarters earlier than this (Figure 6). A year later most, but not all cities were in contraction, and after another year had passed the contraction had receded to primarily coastal cities.

Figure 7 provides yearly snapshots of city contractions between 2000.Q3 and 2004.Q3 and illustrates a geographic pattern of contraction opposite that of Figure 6. In 2000.Q3—one quarter prior to the start of the U.S. employment contraction—10 cities far from the east and west coasts were in contraction. One year later, the contractions had spread to most of the rest of the cites in our sample, and by two years later had begun to recede from the cities on the Atlantic coast. By 2004.Q3, 12 cities were still in contraction, most of which were the same non-coastal cites which had been in contraction in 2000.Q3. The geographic pattern of contractions during this period shared the trait with the early 1990s period that the cities that switched into contraction early also tended to switch out of contraction late. However, the directions of the geographic patterns were completely opposite: The first was an "outside-in" contraction whereas the second was an "inside-out" one.

The geographic pattern for the beginning of the third contractionary period did not resemble that for the previous two. As shown by Figure 8, in 2007.Q1, one year prior to the start of the official recession and two quarters prior to the start of the U.S. employment contraction, 17 cities were already in contraction. These cities were concentrated in California and neighboring states, Florida, and the Rust Belt. As of 2008.Q1, the contraction had spread to many of the cities in the Southeast and to more of the Rust Belt. On the other hand, the Northeast, Northwest, and Mountain regions, along with Texas, were still relatively unscathed. It is too early to make a complete city-level accounting of this contractionary period because it is still far from over as of the time we are writing. Also, additional data might change the picture even of the quarters illustrated by Figure 8.

4. Industrial or Geographic Similarity?

Thus far, we have simply been documenting the differences in city-level contractions without attempting to explain them. To take this next step, we first need a measure of the extent to which cities differ from (or are similar to) one another. The measure we use is related to the concordance of two cities, which is the percentage of time the two cities are in the same business cycle regime (Harding and Pagan, 2002).[9] Formally, the concordance between the employment cycles of cities i and j is:

$$C_{ij} = \frac{100}{T}\sum_{t=1}^{T}\left[S_{it}S_{jt} + (1-S_{it})(1-S_{jt})\right] \tag{2}$$

where S_{it} and S_{jt} are the state variables for cities i and j and T is the number of time periods. As noted in Harding and Pagan (2006), the concordance between two cities is flawed as a measure of business cycle similarity, as it can vary across pairs of cities that have independent employment cycles. Specifically, assuming that S_{it} and S_{jt} are independent, the expected concordance for cities i and j is given by:

$$E_O(C_{ij}) = 1 + 2E(S_{it})E(S_{jt}) - E(S_{it}) - E(S_{jt}), \tag{3}$$

where $E(S_{it}) = (1-q_i)/(2-q_i-p_i)$, $E(S_{jt}) = (1-q_j)/(2-q_j-p_j)$, and the O subscript indicates conditioning on the assumption that S_{it} and S_{jt} are independent. For example, consider two cities with independent employment cycles, and $p_i = p_j = 0.7$. If $q_i = q_j = 0.9$, the expected concordance equals 62.5%, but would climb to 75.5% if $q_i = q_j = 0.95$. Thus, variation in the concordance measure across city pairs may have nothing to do with variation in business cycle comovement, but may instead simply reflect variation in the transition probabilities. For this reason, we focus here on the excess concordance, defined as:

[9] See also Harding and Pagan (2006). Camacho and Perez-Quiros (2006) discuss this approach and propose an alternative framework.

$$XC_{ij} = C_{ij} - E_O\left(C_{ij}\right) + 50. \tag{4}$$

The excess concordance will have an expected value of 50% for any pair of cities with independent business cycles. Each city's average excess concordance and its excess concordance with the U.S. employment cycle is provided in Appendix 1, while the complete set of 1653 city-pair excess concordances is provided in Appendix 2. Figure 9 gives a graphical summary of cities' employment cycles' excess concordances with the U.S. employment cycle.

Why would two cities have widely differing employment cycles? Clearly there are periodic events at the national level that result in most cities experiencing contractions at some point within a period surrounding a national recession. But, around and during these periods, cities enter and exit their own contractions at different times. If city-level switches in and out of contractions were mostly reflections of the industrial composition of cities, then concordance should be high between two cities with similar industrial structures. Likewise, if two geographically similar cities tend to have similar employment cycles, then concordance should be higher for cities within the same region, state, or metro area.

This exercise is related to a longstanding question in the macroeconomics literature about whether fluctuations in aggregate economic variables are driven by microeconomic factors such as industry-level conditions, or aggregate factors that affected all industries (Lilien, 1982; Abraham and Katz, 1986; Caballero, Engel, and Haltiwanger, 1997). The urban/regional analogue of the question splits the analysis along subnational lines, dividing fluctuations into industry, national, state, and regional factors (Clark, 1998; Carlino and Sill, 2001; Del Negro, 2002; Carlino and DeFina, 2004; Owyang, Rapach, and Wall, 2009). Kose, Otrok, and Whiteman (2003) took the question in the other direction, splitting national-level fluctuations into national, continental, and world factors.

Although related to this previous work, which considers a variety of fluctuation types, our question is substantively different because of our characterization of economic fluctuations. The Markov-switching approach characterizes employment fluctuations by the occurrence of expansion and contraction phases and phase-specific growth rates. Our interest presently is in understanding the tendencies of city pairs to be in the same employment cycle phase, regardless of the cities' growth rates within the phases.

To separate the national, regional, state, city, and industry effects, we estimate the following, which regresses business-cycle similarity, as measured by excess concordance, on measures of industrial and geographic similarity:

$$\ln\left(XC_{ij}\right) = \alpha_0 + \alpha_i + \alpha_j + \beta IS_{ij} + \omega_1 PState_{ij} + \omega_2 SState_{ij} + \rho R_{ij} + \lambda Contig_{ij} + \mu_{ij} \qquad (5)$$

In (5), IS_{ij} is a measure of industrial similarity between cities i and j. Our primary measure of industrial similarity is an index that measures the average closeness of employment shares across n major sectors.[10] Denoting the employment share of sector k in city i as x_{ik},

$$IS_{ij} = 1 - \frac{1}{n}\sum_{k=1}^{n}\left|x_{ik} - x_{jk}\right|. \qquad (6)$$

$IS_{ij} \in \left(0,1\right]$ and equals 1 for two cities with identical employment shares for all n sectors. Geographic similarity is measured by four dummy variables: $PState_{ij}$ equals 1 if the principal cities of i and j are in the same state, $SState_{ij}$ equals 1 if the principal city of i is in the same state as outlying counties of j, R_{ij} equals 1 if the principal cities of i and j are in the same census

[10] We use annual data from the BLS for 1990-2008. The sectors are mining, logging, and construction; manufacturing; trade, transportation, and utilities; information; financial activities; professional and business services; education and health services; leisure and hospitality services; other services; and government.

region, and $Contig_{ij}$ equals 1 if cities i and j are contiguous.[11] Our estimation also includes city dummy variables to control for any factor that would affect a city's concordance the same across all other cities.

The results of our estimation of four versions of (5) are provided by Table 2. The first two estimations are extreme versions of the geography vs. industry question. From Model I, which assumes that geographic similarity is unrelated to concordance, we obtain a positive effect for similar industrial structures, but this result is not quite statistically significant at the 5% level ($p \approx 0.06$). From Model II, which assumes that the effect of industrial similarity is zero, we find that cities with principal cities in the same state or region tend to have more-concordant employment cycles. On the other hand, we find no statistically significant relationship for contiguity or our secondary-state dummy.

Of course, geography and industry are likely to be related in that, for a variety of reasons, cities in the same parts of the country will tend to have similar industrial structures. By including only industrial or geographic similarity, as in Models I and II, we are not controlling for this simultaneity. From our results for Model III, which does control for simultaneity, it is clear that the positive role for industrial similarity found in Model I was due mainly to that variable capturing the relationship between geographic similarity and concordance. Specifically, inclusion of industrial similarity has very little effect on our estimates of the link between geography and concordance, but inclusion of the geographic similarity dummies substantially reduces the positive coefficient on industrial similarity from Model I, and raises the p-value for this coefficient to 0.79. We conclude, therefore, that geographically similar cities tend to have

[11] There is a potential variable, $TertiaryState_{ij}$, for when the outlying counties of i and j are in the same state. We only have one pair for which this would equal 1 (Louisville and Cincinnati), so we do not include the variable.

similar employment cycles, but that there is no overall tendency for cities with similar industries to have similar employment cycles.

Model IV is a more-general specification that removes the restriction that the importance of regional similarity is the same across regions. Specifically, Model IV includes four regional-similarity dummies, one for each Census region. It shows that cities in the Midwest region tend to have more-similar employment cycles, but that there is no such relationship for cities in the Northeast, South or West. In addition, Model IV yields a much stronger estimate of the relationship for the Midwest, more than five times the average effect documented in Model III. Note also that Model IV is preferred statistically to Models I – III in that the restrictions needed to obtain those models from IV are easily rejected by likelihood-ratio tests (p-value < 0.001).

We return below to discussing the implications of Model IV, but before doing so we need to check whether our results are sensitive to the way we have measured industrial similarity. We can think of two reasons why our industry similarity index might mask important differences in industrial structure and suppress the importance of industry in explaining concordance. First, the level of aggregation, which is limited by data availability, might be too blunt to capture differences that matter. In particular, our index does not distinguish between the durable and nondurable goods sectors, which might be problematic because the durable goods sector should be more sensitive to monetary policy, for example. Second, perhaps our index, which averages across all sectors, is masking the importance of a subset of sectors. Table 3 summarizes the results we obtain under measures of industrial similarity that ameliorate both of these concerns. Separate data for durable and nondurable sectors are unavailable for three of our cities, so the results in Table 3 are for 55 cities only.

Model IVa simply confirms that we obtain the same general results with our 55 cities as for Model IV with the full sample. Model IVb constructs the industrial similarity index with separate data for durables and nondurables, obtaining almost identical results to Model IVa. Model IVc dispenses with the similarity index and uses measures of similarity for sectors whose sensitivity to the employment cycle should differ from the average: manufacturing and mining, logging, and construction tend to be more sensitive than average, whereas the government sector tends to be less sensitive than average.[12] Nonetheless, we do not find that similarity in any of these sectors is related to concordance. Finally, Model IVd differs from Model IVc in that it looks at durable-goods similarity rather than manufacturing similarity. Again, this has no effect on our results.

To summarize the importance of geographic factors in explaining the pattern of city contractions, the expected excess concordances from Model IV are provided in Table 4. For example, the employment cycles of two cities in different regions and states have an expected excess concordance of 64.2%, as obtained from the intercept term. If the two cities are in the same state in the South, West or Northeast, where regional similarity does not matter, the expected excess concordance rises to 72%. If they are in the same state in the Midwest, where regional similarities matter, the expected excess concordance rises further to 77.9%. So, depending on where the cities are located, geographic similarity can have up to a 13.7 percentage point difference on their expected excess concordance.

Our city dummies can be as important in determining concordance as the geographic factors, as summarized by Table 5, which provides the estimated city effects from Model IV and converts them into percentage points. To prevent perfect collinearity, the city dummies were

[12] For each industry the similarity between cities i and j is $1-|x_{ik}-x_{jk}|$.

restricted to sum to 0, so each shows the difference relative to the average. A positive city effect indicates that, controlling for industrial and geographic similarity, the city tended to display higher excess concordance with others than the average city. The city effect for Phoenix means that their excess concordances with others was nearly 9 percentage point higher, whereas the city effect for Riverside reduced their excess concordances with others by 12 percentage points. The geographic pattern of the city effects is shown by Figure 10. Because the regional effects have been taken out by the four regional dummies, cities with the highest and lowest city effects are scattered across the country. There seems to be some commonality within some states, however, most notably Florida.

These city effects can capture many things, including some that are not necessarily city specific. For example, they might be capturing state-specific effects if the relationship between concordance and being in the same state differs across states. Our state dummy does not distinguish between states, so any state-specific effect that differs from average will be captured by the city effects. The city dummies can also capture how a city's concordance with all other cities differs because of the city's very particular industrial structure. For example, a reasonable explanation for the large negative city effects for Detroit, Warren, San Diego, and Virginia Beach is that they have very specific industries that set them apart: automobile manufacturing in the cases of Detroit and Warren, and large military bases in the cases of San Diego and Virginia Beach. So, although these industries are important in explaining the employment cycles of their particular cities, they are not prevalent enough across cities to explain the geographic patterns depicted above.

5. Geography vs. Other Similarities

Our results above indicate that cities within the same state and perhaps the same region tend to have similar employment cycles. These results are driven either by the existence of spatial propagation whereby switches in and out of contractions spread via some underlying spatial links between cities, or cities in the same state or region tend to share certain characteristics that we have not controlled for. In this section we examine whether any of four sets of variables capturing similarities in human capital, monetary-policy channels, industrial diversity, and agglomeration are related to concordance.[13] Further, if they are related, we can compare their inclusion in the estimation on our estimates of geographic factors to see if they are driving our findings. The results of this exercise are provided in Table 6.

For the first set of results—Model V—we add three measures of human capital similarity to Model IV: a racial similarity index constructed along the lines of the industrial similarity index, and two measures of educational similarity (high school and bachelor's degree attainment) constructed along the lines of the single-industry similarity measures used above.[14] We know from previous research that cities' performance in either phase of the employment cycle is related to human capital as measured by education and race (Owyang, Piger, Wall, and Wheeler, 2008), and that the employment effects of recessions differ by race and education level (Hoynes, 2000; Engemann and Wall, 2010). Our question here is a bit different from this: Do similarities between cities in their racial composition and educational attainment make them more likely to be in the same phase of the employment cycle? Figures 11 and 12, which plot employment by

[13] The data for these variables are from the Census Bureau's State and Metropolitan Area Data Book: 2006, which included online updates as of February 9, 2009. This source typically provides data for one year because of changes in the composition of cities over time.

[14] We use four racial categories: white, black, Asian or Pacific Islander, and Native American. High school attainment is the share of the population over 25 years of age who have a high school diploma and have no additional education. Bachelor's degree attainment is the share of the same group with at least a bachelor's degree. All variables are for 2006.

race and educational attainment over our sample period, illustrate why one might think this to be so.

Note the period surrounding the aggregate employment contraction of the early 2000s (Figure 11): Black employment started falling in 1999, prior to the start of the aggregate contraction, whereas white employment peaked in 2001, after the aggregate contraction had begun. This suggests that cities with relatively similar racial compositions might have had relatively similar employment cycles, although the less-clear pattern around other turning points suggests otherwise. The differences between levels of educational attainment in the employment effects of contractions are more stark than those between races (Figure 12): The drop in employment for those with at least a bachelors degree is almost imperceptible whereas steep and early drops and late recoveries are the norm for those with only a high school diploma.[15] All else constant, cities with a labor force that has relatively many with only a high school diploma should, therefore, have a significantly different employment cycle from those with relatively many with at least a bachelors degree. As summarized by Table 6, when we add our human capital variables to Model IV, only the similarity in high school attainment is positive and statistically significant: Two cities with similar levels of high school attainment tend to have more-concordant employment cycles.

Previous research has found that the effects of monetary policy differ across states and regions (Carlino and DeFina, 1998 and 1999), so it is possible that the city-level differences in employment cycles are driven in part by varying responses to monetary policy shocks. To capture differences in the magnitudes of various channels of monetary policy, Model VI adds three variables to Model V. The money channel, whereby monetary policy has larger effects on

[15] Note that these are the only education and racial categories available at a quarterly frequency and that the data on educational attainment begin in 1992.

manufacturing than other industries, is already captured by our industry-similarity variable. To capture the broad credit channel, through which large firms are better able to absorb monetary policy shocks because of lower information and transactions costs, we have included the similarity in mean establishment size. Through the narrow credit channel small banks are thought to be more limited than large banks in finding alternative funding under tight monetary policy, so we have included two bank-size measures. The first, average bank size—deposits per bank—represents this channel directly, and the second, banks per establishments, represents the availability of banking options for firms within a city. As shown in Table 6, we find evidence that the broad money channel is related to city business-cycle similarity in that the sign on the similarity of mean establishment size is positive and statistically significant.

The final two models, VII and VIII, examine whether employment cycle similarities can be attributed to similarities in industrial diversity and agglomeration, respectively. Simon (1988) found that a more industrially diversified city will have less frictional employment because its labor force will be more able to adjust to any negative shock. In our context, this might mean that two cities that are similarly diversified should have similar employment cycles because they could adjust more quickly during a contraction. Model VII demonstrates that the similarity of industrial diversity is positively related to concordance, and this effect is statistically significant at the 5% level. Finally, to test whether similarly agglomerated cities tend to have similar employment cycles, we estimated Model VIII, which adds similarity of city density and city size to Model VI. Neither variable is close to being statistically significant.

Models VII and VIII include each of the statistically significant variables from all specifications we have considered, with Model VII preferred to Model VIII based on a likelihood ratio test. The same geographic variables that were significant in Model IV are still significant in

Model VII, with only minor changes in their magnitudes. From Model VII we conclude that employment-cycle similarity is related to similarity in geography, industrial diversity, high school attainment, and mean establishment size.

To see the extent to which these similarities matter, Table 7 calculates the expected concordances under the various combinations of these similarities. The first column of results, which is analogous to Table 4, assumes that two cities have the sample-average similarities in high school attainment, mean establishment size, and industrial diversity but can differ geographically. Note first that for two such cities in different regions and states, the expected excess concordance is 63.8. If the two cities were in the same state in the South, West or Northeast, they should have an excess concordance of 71.2. If they are in different Midwestern states their expected excess concordance is 68.5, while if they are in the same Midwestern state, their expected excess concordance rises to 76.5.

The second through fourth columns of results assume, respectively, that the two cities have the same levels of high school attainment, establishment size and industrial diversity. Having the same level of each of these attributes adds, by itself, between 0.6 to 1.0 percentage points to the expected excess concordances in the first column of results. The final column assumes that the cities have the same level of each of these attributes, and results in concordances that are 2.3 to 2.8 percentage points larger than those in the first column of results. Thus, our addition of human capital, monetary policy, and industrial diversity variables contributes something, but not a whole lot, to our explanation of city concordances. In contrast, geographic similarity is still explaining large chunks of the differences in concordance.

The large effect of geographic similarity on city-level business cycle comovement is striking. It is possible that this effect is proxying for some city-level characteristics that we have not considered here. Alternatively, the geographic similarity is picking up a spatial propagation mechanism by which turns in the employment cycle are spread from city to city. One likely such mechanism is the intensity of trade relationships, which is known to be strongly related to the distance between U.S. trading regions, as well as display a home-state bias.[16]

6. Summary and Conclusions

We estimated city-level employment cycles for 58 large U.S. cities and documented the substantial cross-city variation in the timing, lengths, and frequencies of their employment contractions. We also showed how the spread of city-level contractions associated with U.S. recessions has tended to follow recession-specific geographic patterns. Cities within the same state or region have tended to have similar employment cycles, but cities with similar industrial mixes did not. Additionally, cities with more-similar high school attainment, mean establishment size, and industrial diversity have tended to have more-similar employment cycles. According to our statistically preferred model, geographic similarity can raise the percentage of time that two cities are in the same business cycle phase by as much as 13.2 percentage points. For any degree of geographic similarity, having identical high school attainment, mean establishment size and industrial diversity will raise the percentage of time two cities are in the same business cycle phase by as much as 2.8 percentage points.

[16] See, for example, Wolf (2000), Hillberry and Hummels (2003, 2008).

Appendix 1. Summary Statistics

	Contraction Frequency	Mean Excess Concordance	Excess Concordance with U.S.
Atlanta-Sandy Springs-Marietta, GA	0.361	71.7	78.7
Austin-Round Rock, TX	0.167	62.5	77.7
Baltimore-Towson, MD	0.292	67.8	75.9
Bethesda-Gaithersburg-Frederick, MD	0.514	68.9	76.0
Boston-Quincy, MA	0.278	67.2	75.1
Buffalo-Niagara Falls, NY	0.389	68.7	84.3
Charlotte-Gastonia-Concord, NC-SC	0.278	70.1	64.6
Chicago-Naperville-Joliet, IL	0.264	68.3	77.6
Cincinnati-Middletown, OH-KY-IN	0.681	61.7	77.9
Cleveland-Elyria-Mentor, OH	0.569	67.5	87.7
Columbus, OH	0.444	66.5	81.0
Dallas-Plano-Irving, TX	0.208	68.5	72.3
Denver-Aurora, CO	0.153	62.6	73.8
Detroit-Livonia-Dearborn, MI	0.681	61.4	76.5
Edison, NJ	0.083	54.9	79.4
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	0.278	62.7	64.6
Fort Worth-Arlington, TX	0.264	69.4	85.1
Hartford-West Hartford-East Hartford, CT	0.472	61.6	61.8
Houston-Sugar Land-Baytown, TX	0.333	68.9	62.1
Indianapolis-Carmel, IN	0.194	66.7	57.0
Jacksonville, FL	0.333	71.5	68.2
Kansas City, MO-KS	0.347	65.8	70.1
Las Vegas-Paradise, NV	0.306	70.3	73.0
Los Angeles-Long Beach-Glendale, CA	0.347	67.6	69.3
Louisville-Jefferson County, KY-IN	0.194	63.5	83.9
Memphis, TN-MS-AR	0.528	69.1	80.5
Miami-Miami Beach-Kendall, FL	0.236	68.6	78.3
Milwaukee-Waukesha-West Allis, WI	0.236	70.3	62.1
Minneapolis-St. Paul-Bloomington, MN-WI	0.403	71.0	59.2
Nashville-Davidson--Murfreesboro, TN	0.194	64.5	76.0
Nassau-Suffolk, NY	0.139	55.3	66.3
Newark-Union, NJ-PA	0.181	57.4	61.9
New Orleans-Metairie-Kenner, LA	0.472	61.4	75.6
New York-White Plains-Wayne, NY-NJ	0.292	67.9	68.0
Oakland-Fremont-Hayward, CA	0.597	62.7	79.7
Oklahoma City, OK	0.139	64.2	65.6
Orlando-Kissimmee, FL	0.264	70.6	74.6
Philadelphia, PA	0.306	69.0	57.2
Phoenix-Mesa-Scottsdale, AZ	0.417	73.2	80.3
Pittsburgh, PA	0.292	68.2	81.6
Portland-Vancouver-Beaverton, OR-WA	0.194	68.2	78.8
Providence-New Bedford-Fall River, RI-MA	0.194	61.7	71.3
Richmond, VA	0.236	68.9	70.1
Riverside-San Bernardino-Ontario, CA	0.264	54.2	64.2
Rochester, NY	0.375	67.4	68.0
Sacramento-Arden-Arcade-Roseville, CA	0.236	54.4	74.8
St. Louis, MO-IL	0.264	69.0	65.4
Salt Lake City, UT	0.167	62.4	77.0
San Antonio, TX	0.319	64.9	81.6
San Diego-Carlsbad-San Marcos, CA	0.667	59.7	88.6
San Francisco-San Mateo-Redwood City, CA	0.458	63.4	71.2
San Jose-Sunnyvale-Santa Clara, CA	0.208	70.9	71.0
Santa Ana-Anaheim-Irvine, CA	0.347	63.4	71.9
Seattle-Bellevue-Everett, WA	0.181	66.9	80.2
Tampa-St. Petersburg-Clearwater, FL	0.347	70.8	71.4
Virginia Beach-Norfolk-Newport News, VA-NC	0.028	57.3	71.8
Warren-Troy-Farmington Hills, MI	0.486	62.5	77.1
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.125	56.5	77.3
Cross-City Average	0.285	65.4	73.3
United States	0.276		

Appendix 2. Cross-City Excess Concordances (Ordered by City Size)

	Los Angeles	Chicago	Houston	Atlanta	Washington	Dallas	Philadelphia	Phoenix	Minneapolis	Boston	Snta Ana-Anah	Seattle	St. Louis	Baltimore	Warren	Tampa	San Diego	Nassau-Suffolk	Riverside	Denver	Pittsburgh	Cleveland	San Francisco	Orlando	San Jose	Miami	Oakland	Edison	Portland	Cincinatti	Newark	Kansas City	Columbus	Las Vegas	Detroit	Indianapolis	Sacramento	Fort Worth	Milwaukee	Charlotte	San Antonio	Fort Lauderdale	Virginia Beach	Austin	Nashville	Salt Lake City	Memphis	Richmond	Jacksonville	Louisville	New Orleans	Providence	Bethesda	Hartford	Oklahoma City	Buffalo	Rochester
New York	80	73	78	71	59	78	78	81	68	71	69	69	74	77	54	71	63	59	54	62	68	66	72	69	79	75	65	53	72	63	61	64	62	71	64	67	54	73	72	74	63	61	55	61	64	62	69	71	74	63	63	58	74	75	69	79	73
Los Angeles		71	74	69	63	76	77	78	66	71	79	70	72	75	49	70	69	63	67	61	64	61	79	69	76	74	69	58	69	59	62	63	58	70	59	66	61	70	69	72	62	63	60	61	65	61	65	72	72	61	58	62	70	78	68	75	71
Chicago			78	79	56	72	78	73	76	77	61	72	82	72	63	71	61	53	46	67	76	66	69	72	79	78	62	56	74	60	58	72	70	71	61	73	45	75	75	82	71	64	57	67	67	70	69	73	71	66	60	60	72	67	68	70	67
Houston				75	61	77	83	74	72	74	64	68	79	76	62	68	64	61	48	65	76	70	77	67	85	77	65	56	70	69	66	73	68	68	66	67	49	74	70	78	74	59	55	65	63	68	74	70	70	62	70	57	71	68	68	71	70
Atlanta					57	69	75	81	86	75	66	71	79	71	74	82	63	54	51	68	76	77	69	84	80	75	63	57	73	70	58	81	75	76	69	76	51	77	79	81	80	70	62	68	75	69	82	79	81	71	72	72	79	62	66	68	67
Washington						60	59	63	55	55	63	54	58	62	43	60	47	66	62	45	53	52	52	58	61	60	49	63	57	47	71	50	49	60	48	58	61	57	57	58	47	63	66	45	57	45	55	61	63	48	49	61	57	56	55	63	59
Dallas							78	76	66	71	65	74	73	77	55	70	58	60	59	70	72	66	68	71	78	75	67	54	77	57	61	63	65	76	57	69	58	78	77	73	63	60	55	70	64	70	67	70	75	71	66	57	69	71	74	77	77
Philadelphia								77	73	74	66	69	79	77	59	70	65	59	51	64	73	70	74	69	84	75	66	54	71	64	64	69	66	71	65	69	50	75	72	79	69	61	55	64	64	67	74	71	73	63	64	57	76	72	68	75	72
Phoenix									86	72	78	70	73	78	68	91	70	63	68	65	66	79	70	82	79	75	69	58	72	74	60	71	72	85	73	68	69	76	77	75	68	74	61	65	71	63	84	78	87	67	68	71	89	71	69	81	76
Minneapolis										73	66	68	77	68	79	87	70	52	56	66	73	82	66	81	74	73	70	55	70	74	52	75	83	81	73	70	59	75	76	79	74	72	59	66	69	66	86	76	81	65	65	69	86	59	64	69	69
Boston											60	74	78	71	63	70	58	51	45	68	75	63	65	74	75	77	60	57	76	57	54	72	67	70	59	72	44	74	77	78	70	63	59	68	69	69	66	72	71	68	57	62	69	66	67	70	67
Snta Ana-Anah												59	61	67	49	73	69	64	78	50	53	61	68	69	65	63	69	58	58	59	62	55	58	73	59	61	73	60	61	61	51	72	63	50	63	51	65	69	75	50	55	71	70	67	57	67	63
Seattle													73	70	64	69	51	51	49	78	77	59	64	76	72	74	57	57	81	50	52	71	64	72	50	71	46	77	82	75	71	59	60	78	72	75	60	73	72	79	59	62	62	64	76	70	74
St. Louis														73	63	72	61	55	46	68	77	66	70	73	80	79	62	57	75	60	59	73	70	72	61	73	46	76	76	83	72	65	59	68	68	71	69	74	72	67	60	61	72	67	70	71	68
Baltimore															53	74	56	62	52	64	68	65	70	73	80	74	57	56	73	58	65	65	59	72	59	68	52	74	73	75	65	62	57	64	66	61	68	75	77	65	62	62	76	75	68	75	76
Warren																70	68	42	42	64	71	86	52	70	62	61	70	47	66	78	46	70	86	67	81	65	46	63	66	64	74	59	52	64	63	64	78	62	66	64	67	59	66	41	59	59	63
Tampa																	64	57	63	63	66	76	61	84	72	73	65	57	71	69	56	71	74	88	68	71	63	75	77	74	66	76	62	63	70	61	80	79	88	66	65	72	83	63	67	74	73
San Diego																		48	62	48	60	79	77	56	65	56	93	43	49	76	52	51	79	64	73	53	58	55	52	59	58	56	44	48	47	51	74	56	60	42	51	51	68	55	51	61	63
Nassau-Suffolk																			63	42	51	53	52	55	61	57	51	60	54	48	71	48	48	58	50	56	61	54	55	55	45	61	63	42	55	42	56	58	61	45	50	58	58	57	52	64	60
Riverside																				44	44	54	56	57	50	48	70	57	49	50	61	40	54	69	49	48	85	50	51	46	36	65	62	43	47	44	55	54	63	43	45	61	60	52	50	60	56
Denver																					74	59	58	70	68	67	58	47	75	50	45	68	63	66	52	65	46	73	75	71	66	53	52	78	65	76	59	66	66	78	58	55	62	59	71	66	65
Pittsburgh																						72	70	73	78	73	67	56	79	62	61	71	77	69	62	74	44	78	79	79	80	57	56	73	67	74	73	71	69	71	69	61	64	61	69	69	68
Cleveland																							63	70	73	62	81	48	61	89	58	68	89	73	84	68	58	69	66	67	71	62	49	59	63	59	92	65	75	62	72	59	78	52	59	71	75
San Francisco																								60	79	66	77	47	63	62	57	61	58	59	62	58	48	68	64	72	67	49	46	58	57	59	68	63	64	56	58	51	67	73	59	70	66
Orlando																									71	74	60	61	78	61	54	75	70	82	60	75	57	77	84	75	71	72	66	70	74	67	72	81	87	73	67	76	74	63	68	71	72
San Jose																										76	65	56	74	66	67	72	67	70	66	69	50	78	74	82	75	60	56	68	67	68	77	74	75	66	67	61	77	73	69	76	74
Miami																											58	59	77	58	58	72	66	73	59	72	48	75	77	79	69	66	60	67	70	67	65	76	73	69	61	63	68	69	71	72	70
Oakland																												46	56	75	53	51	84	70	71	57	67	62	58	60	59	57	46	58	48	61	73	58	63	52	56	53	67	54	58	64	69
Edison																													60	42	65	53	50	58	45	61	56	54	60	58	50	64	68	47	60	48	50	61	58	51	44	63	52	51	52	58	54
Portland																														51	54	70	66	74	57	73	48	79	84	78	70	61	60	75	71	72	62	75	74	76	66	65	64	66	73	72	73
Cincinatti																															51	69	78	63	83	61	54	60	57	61	65	55	43	50	57	50	86	58	65	53	75	53	73	51	50	66	65
Newark																																49	54	56	52	60	61	55	54	59	54	60	66	45	55	48	61	59	59	46	55	60	58	54	54	63	58
Kansas City																																	62	65	60	76	40	71	76	76	76	59	61	67	77	68	75	73	70	73	70	63	69	57	63	63	62
Columbus																																		79	76	68	58	68	69	69	68	68	53	63	57	66	80	67	70	59	64	61	71	48	63	64	70
Las Vegas																																			63	71	69	75	77	71	61	76	62	66	64	66	75	77	85	66	65	70	77	61	73	72	73
Detroit																																				58	54	60	57	62	66	60	45	52	55	51	79	59	66	50	70	54	70	55	51	67	64
Indianapolis																																					49	72	76	73	71	64	64	65	74	68	69	76	70	73	65	66	63	57	66	66	70
Sacramento																																						50	51	45	35	65	61	46	47	46	59	54	63	46	49	61	64	50	52	61	57
Fort Worth																																							82	79	71	60	55	73	69	70	70	73	78	74	66	60	72	68	74	77	77
Milwaukee																																								78	73	64	63	75	74	73	67	78	79	79	66	68	70	66	74	75	76
Charlotte																																									75	64	59	71	71	71	71	77	74	69	61	64	73	69	70	72	70
San Antonio																																										54	54	66	71	66	75	67	67	70	66	56	66	59	62	65	63
Fort Lauderdale																																											69	53	66	54	63	70	76	54	56	74	66	54	60	63	59
Virginia Beach																																												52	66	52	52	67	62	54	46	70	55	50	56	56	53
Austin																																													64	76	59	65	66	77	58	55	62	59	71	66	65
Nashville																																														62	67	71	70	74	60	69	64	60	63	68	63
Salt Lake City																																															59	63	64	75	58	52	62	57	72	63	63
Memphis																																																68	76	63	78	62	83	57	60	70	68
Richmond																																																	79	67	61	72	71	66	67	70	70
Jacksonville																																																		69	72	73	79	68	70	76	76
Louisville																																																			64	57	60	58	73	67	68
New Orleans																																																				56	61	52	61	62	60
Providence																																																					65	54	53	61	58
Bethesda																																																						68	62	75	70
Hartford																																																							63	77	65
Oklahoma City																																																								69	69
Buffalo																																																									79

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Figure 1.

Employment-Contraction Probability for the United States
Shaded Areas are NBER Recessions

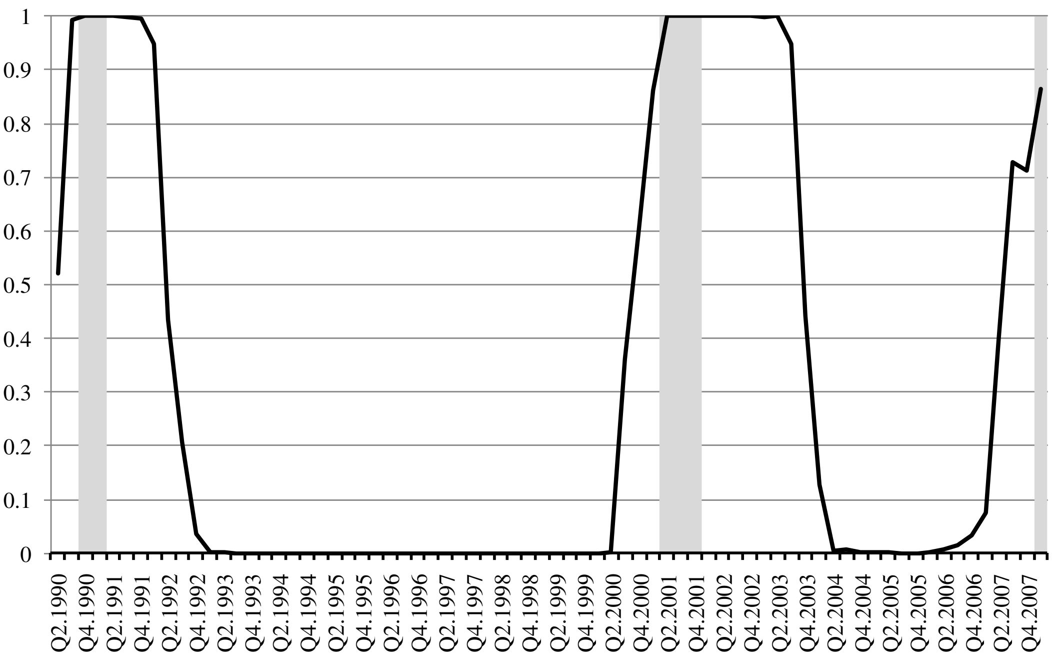


Figure 2. Employment-Contraction Probabilities for the Six Largest Cities

Shaded Areas are U.S. Employment Contractions

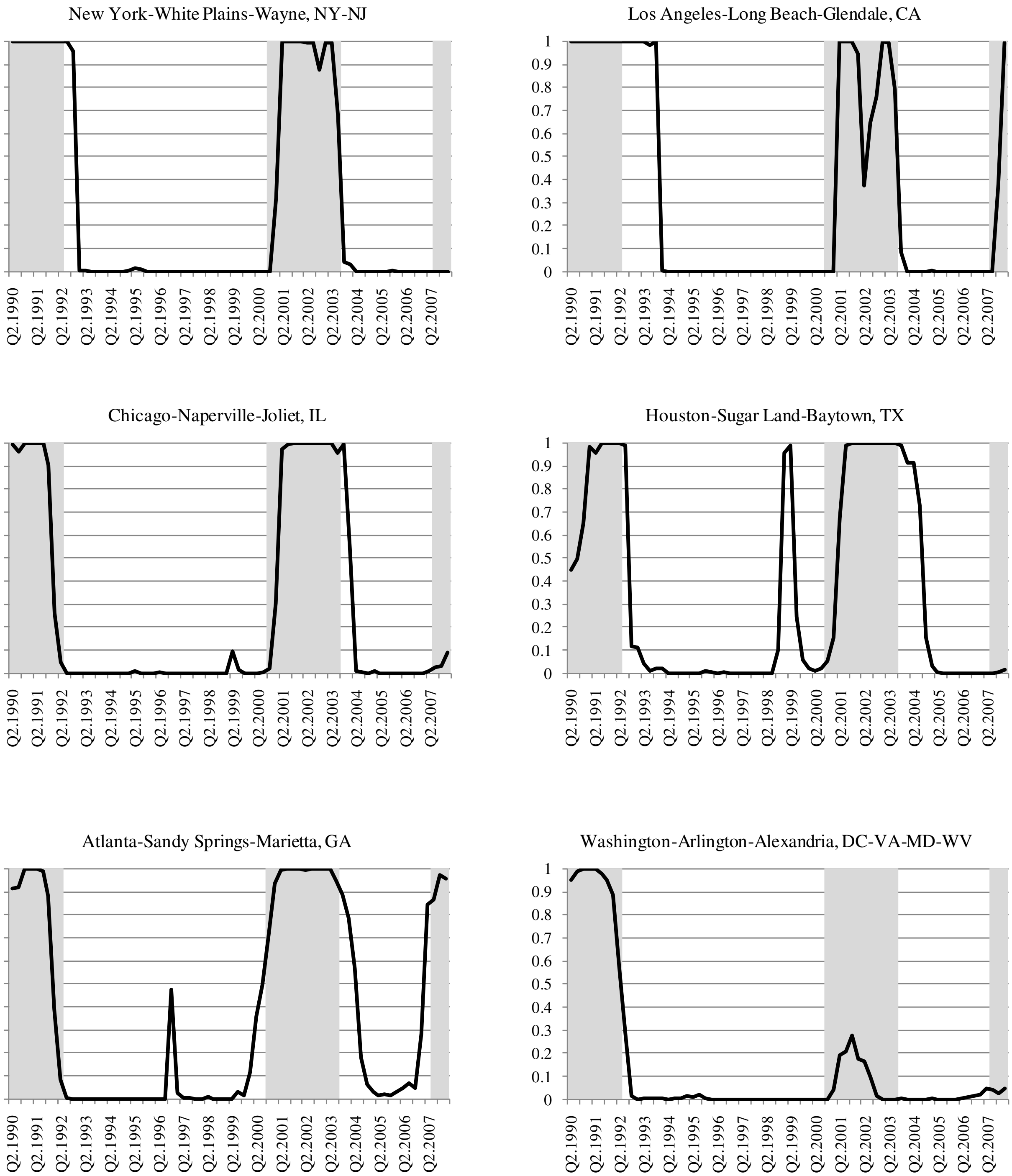


Figure 3. Employment-Contraction Probabilities for the Six Smallest Cities

Shaded Areas are U.S. Employment Contractions

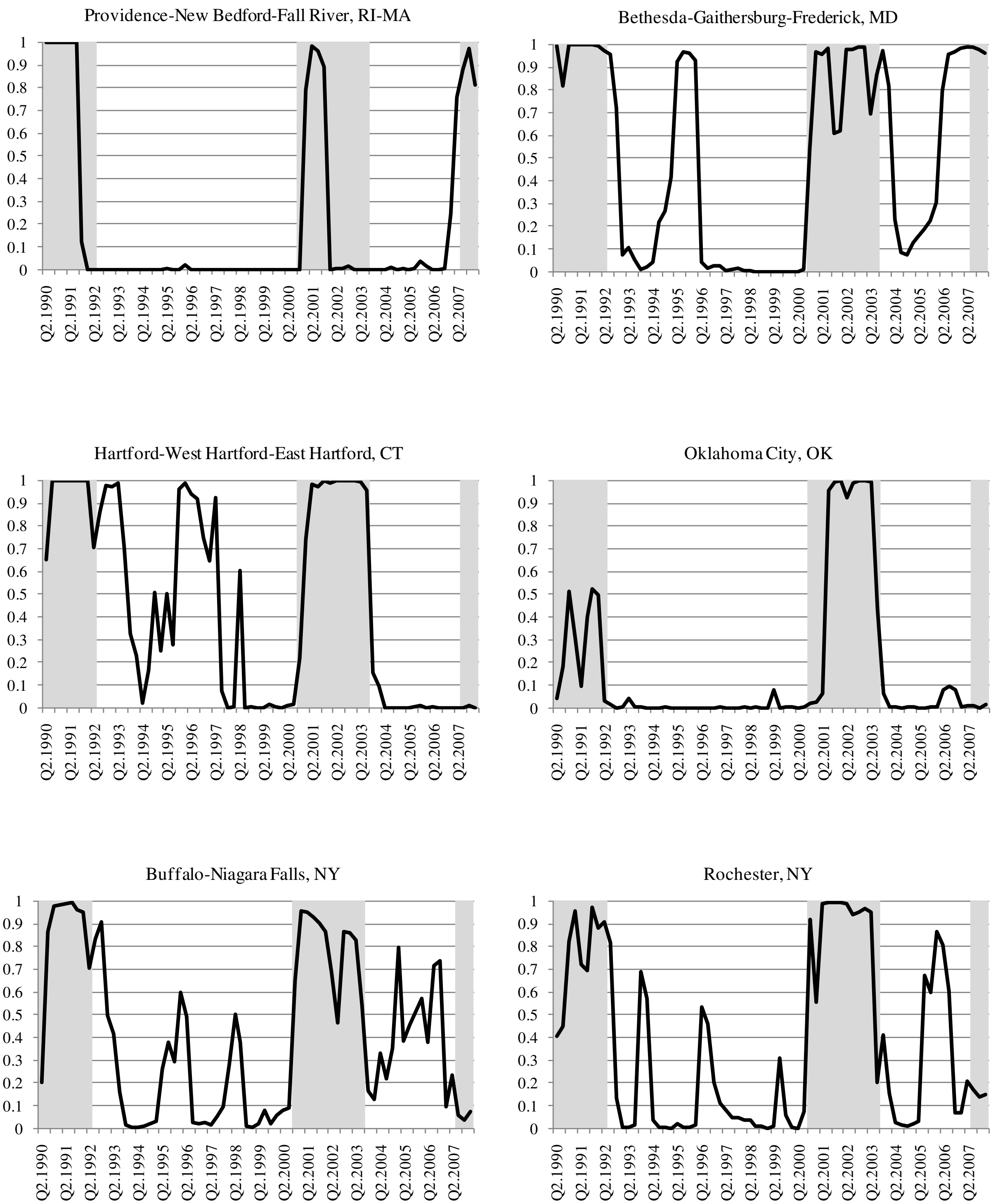


Figure 4.

Frequency of Recession Across Cities, 1990-2008
(Percentage of Time in Contraction)

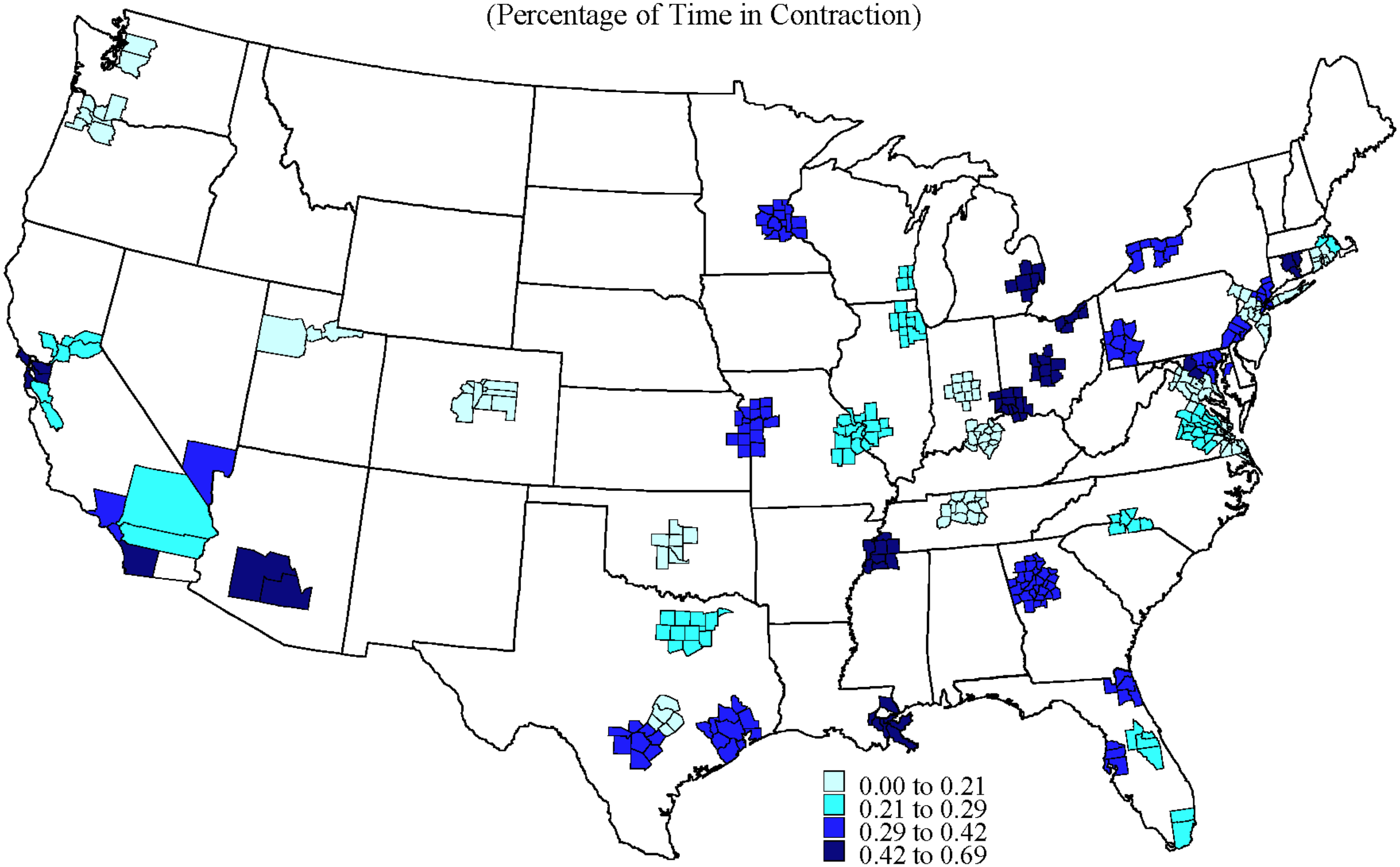


Figure 5.

Number of Cities in Contraction
Light Gray Areas Indicate U.S. Employment Contractions
Dark Gray Areas Indicate NBER Recessions

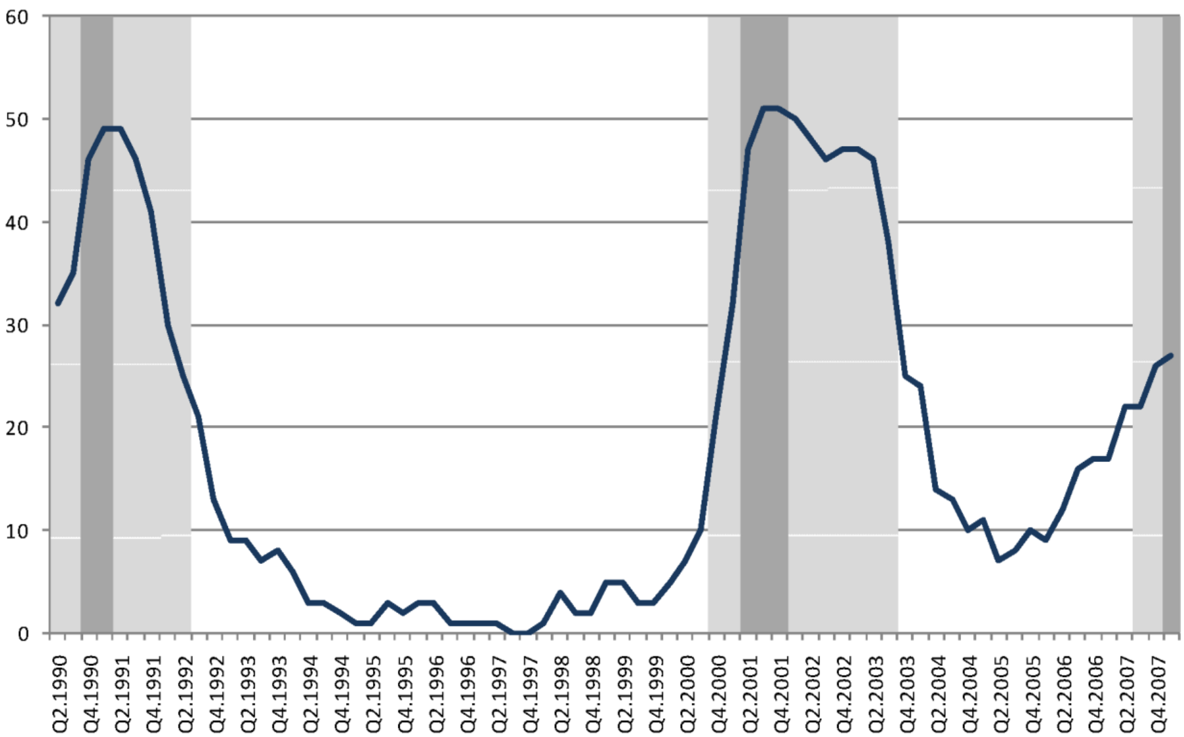
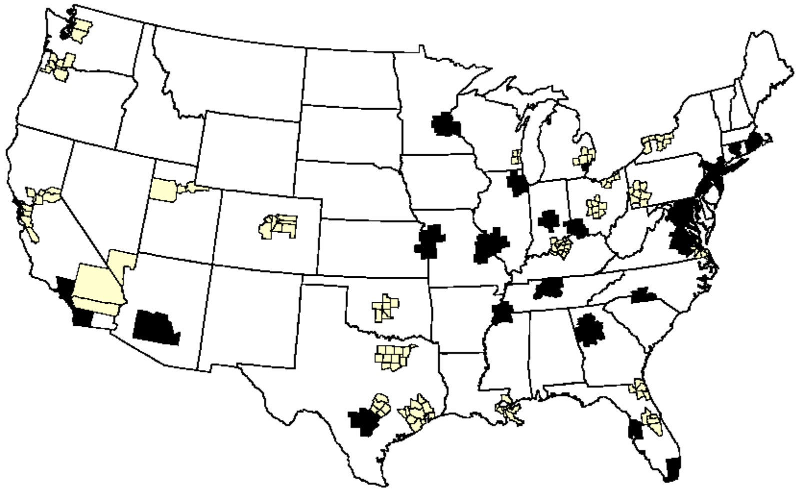
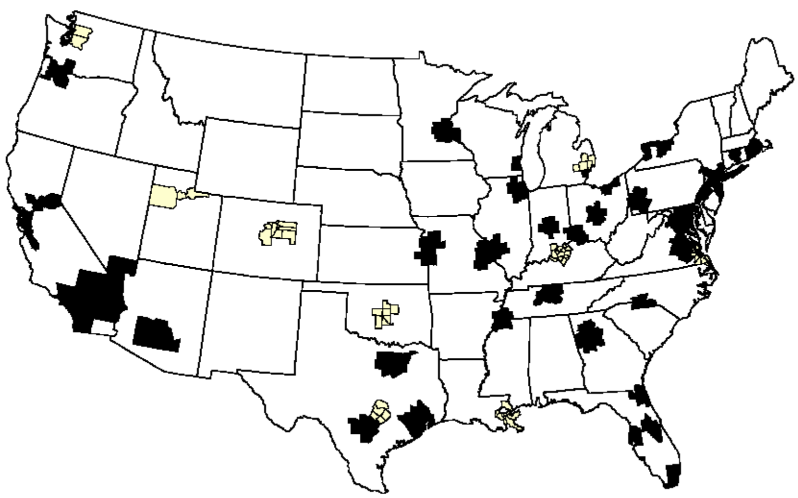


Figure 6. Early 1990s Contractions
Cities in Contraction are in Black

1990.Q2



1991.Q2



1992.Q2

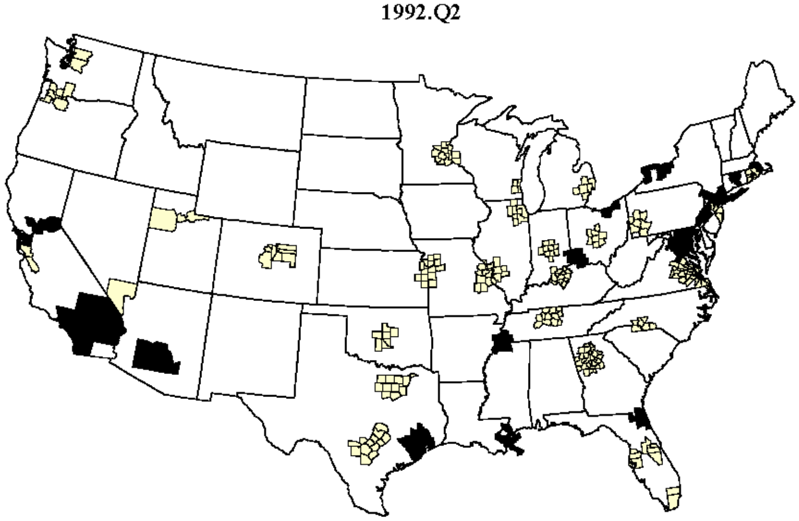
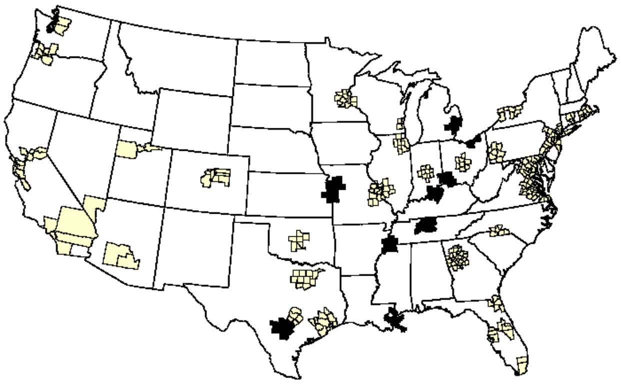
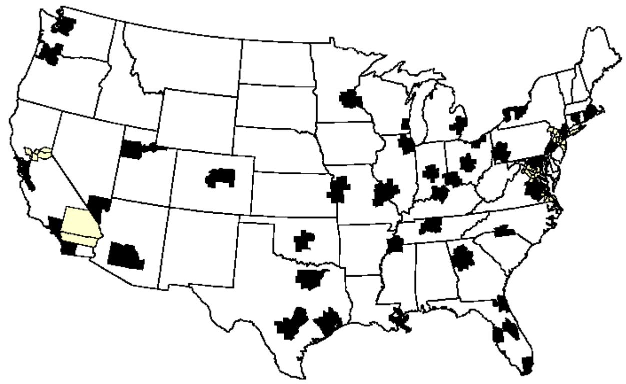


Figure 7. Early 2000s Contractions
Cities in Contraction are in Black

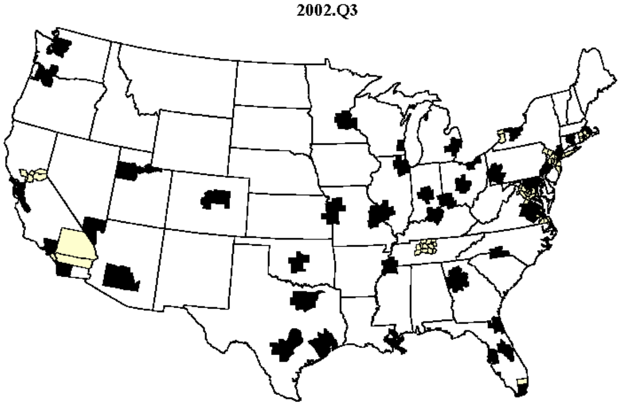
2000.Q3



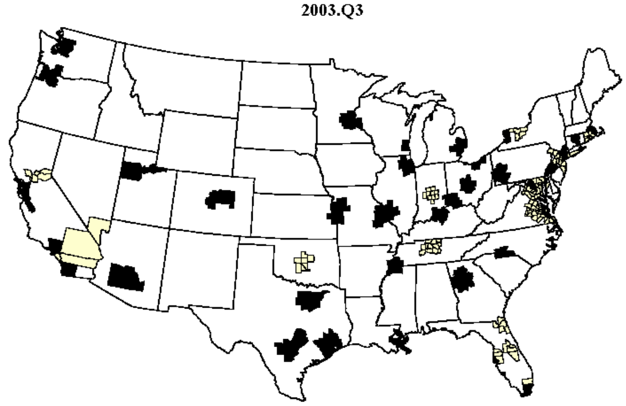
2001.Q3



2002.Q3



2003.Q3



2004.Q3

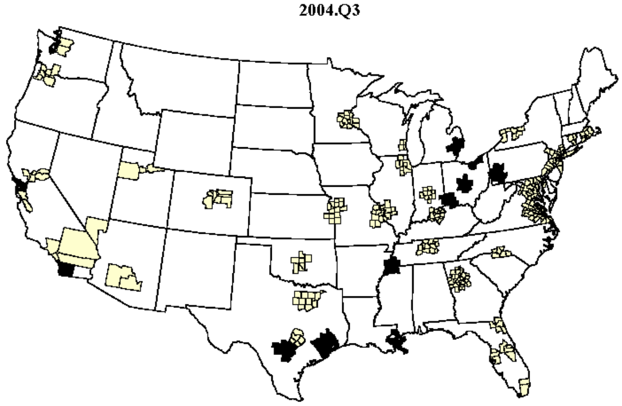
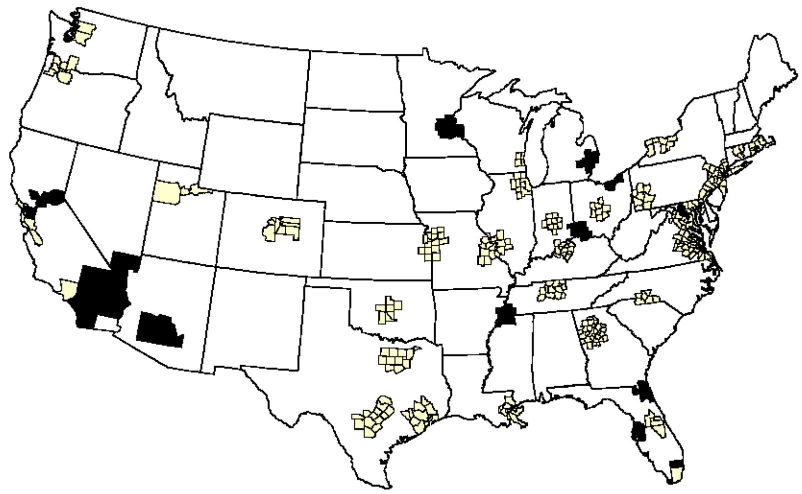


Figure 8. Late 2000s Contractions
Cities in Contraction are in Black

2007.Q1



2008.Q1

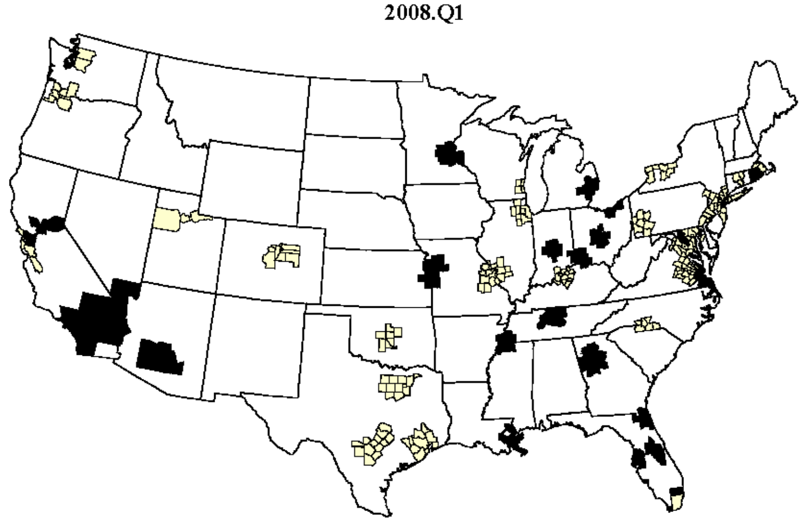


Figure 9. Excess Concordance with the United States

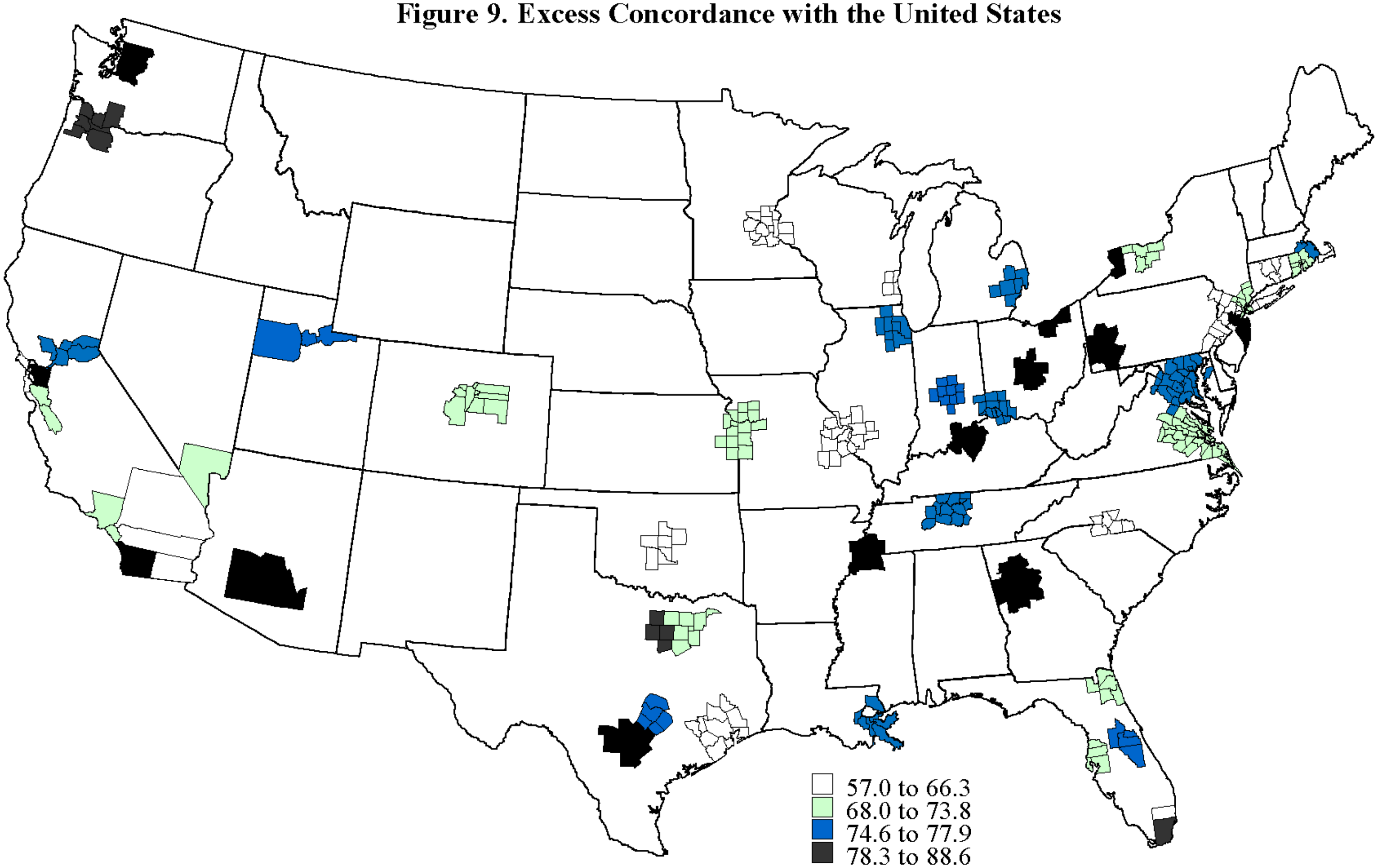


Figure 10. City Effects in Percentage Points

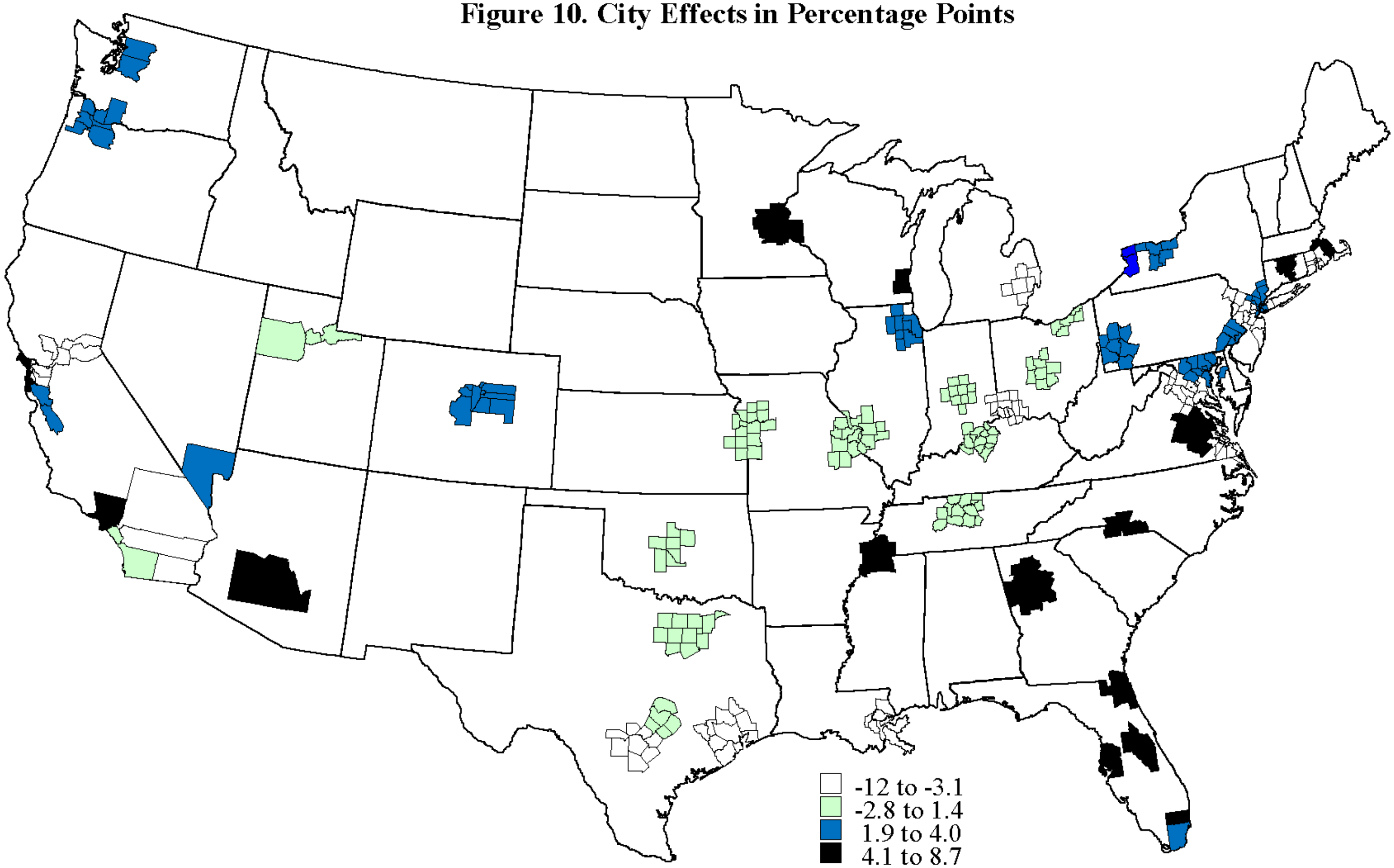


Figure 11. Employment by Race
Shaded Areas Indicate U.S. Employment Contractions

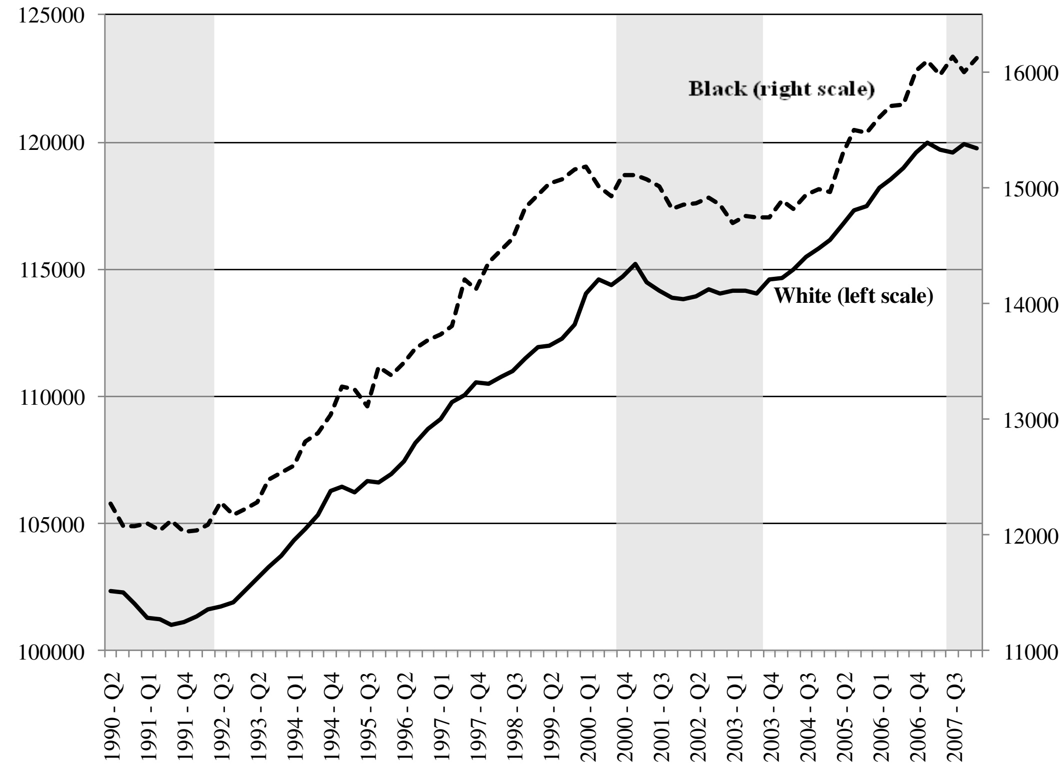


Figure 12. Employment by Educational Attainment
Shaded Areas Indicate U.S. Employment Contractions

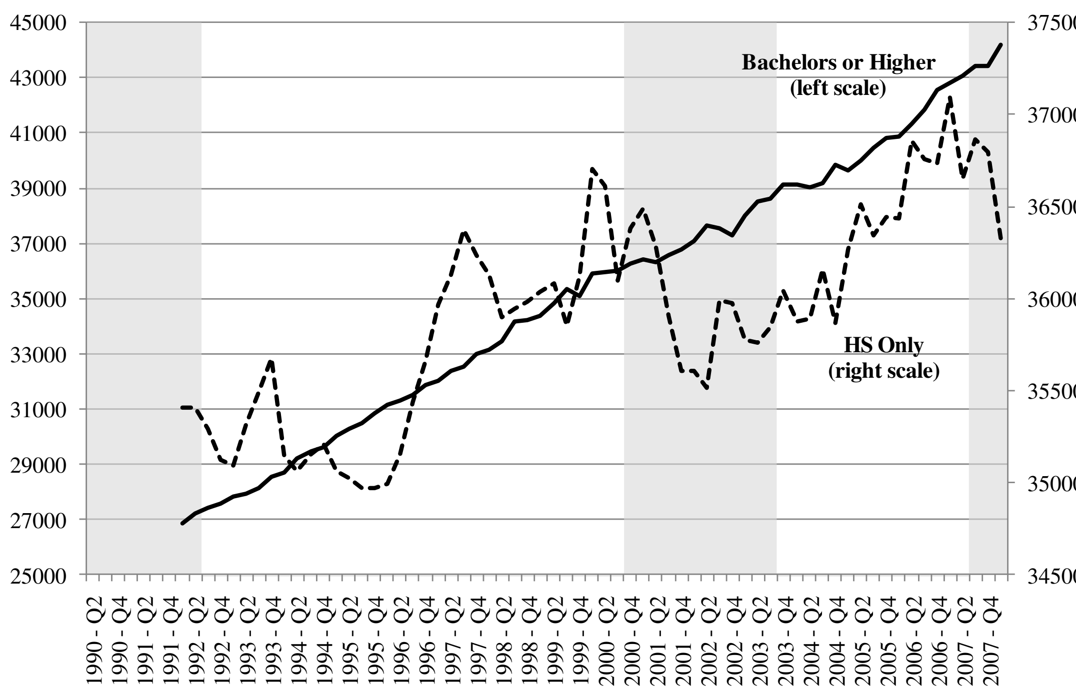


Table 1. The Occurrence of City-Level Contractions

A █ indicates a contractionary quarter, and shaded areas are U.S. contractions

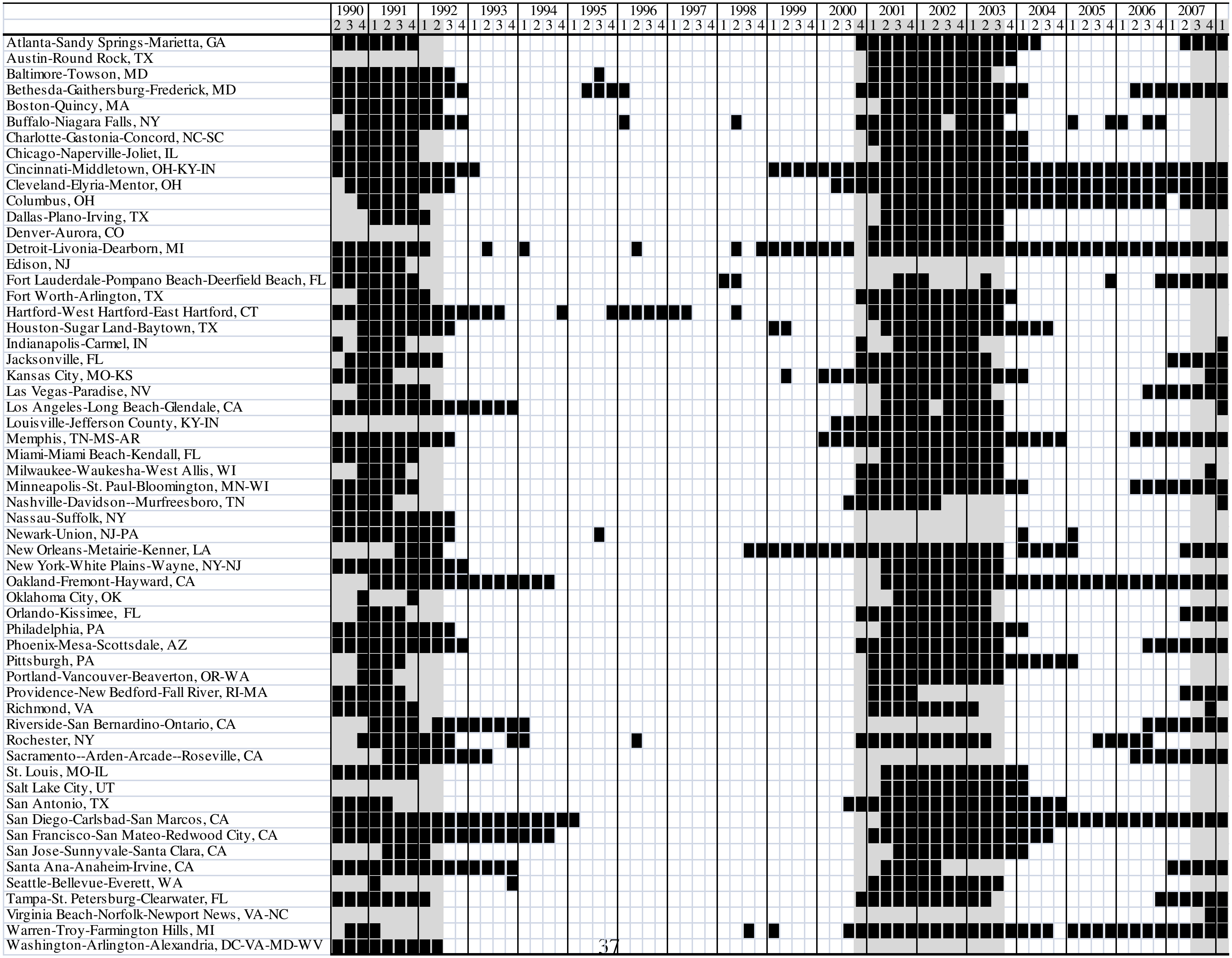


Table 2. Industrial vs. Geographic Similarity

	I	II	III	IV
Industrial Similarity Index	0.9325		0.1283	-0.0211
	(0.4997)		(0.4910)	(0.4842)
Same Principal State		0.1146*	0.1144*	0.1150*
		(0.0217)	(0.0217)	(0.0208)
Same Secondary State		-0.0072	-0.0076	-0.0169
		(0.0277)	(0.0277)	(0.0283)
Same Region		0.0152*	0.0149*	
		(0.0065)	(0.0065)	
Both in Northeast				0.0271
				(0.0190)
Both in South				-0.0126
				(0.0099)
Both in Midwest				0.0789*
				(0.0192)
Both in West				0.0115
				(0.0166)
Contiguous		0.0403	0.0400	0.0434
		(0.0304)	(0.0305)	(0.0303)
Constant	4.1942*	4.1602*	4.1637*	4.1616*
	(0.0138)	(0.0029)	(0.0137)	(0.0135)

The dependent variable is the log of the excess concordance between the two cities, all five models include city dummies, and all independent variables except for dummies are in logs. Statistical significance at the 5 percent level is indicated by "*". Standard errors are White-corrected.

Table 3. Robustness Across Measures of Industrial Similarity

	IVa	IVb	IVc	IVd
Industrial Similarity	0.0546			
	(0.5319)			
Industrial Similarity		0.0077		
(durables and nondurables)		(0.5483)		
Mining, Logging, and			0.0572	0.0542
Construction Similarity			(0.0970)	(0.0953)
Government Similarity			0.3300	0.3187
			(0.2091)	(0.2095)
Manufacturing Similarity			-0.1412	
			(0.0906)	
Durables Similarity				-0.1494
				(0.1232)
Same Principal State	0.1198*	0.1198*	0.1178*	0.1171*
	(0.0238)	(0.0239)	(0.0231)	(0.0230)
Same Secondary State	-0.0175	-0.0174	-0.0179	-0.0174
	(0.0296)	(0.0296)	(0.0297)	(0.0297)
Both in Northeast	0.0205	0.0208	0.0200	0.0198
	(0.0194)	(0.0194)	(0.0194)	(0.0194)
Both in South	-0.0061	-0.0061	-0.0046	-0.0041
	(0.0103)	(0.0103)	(0.0102)	(0.0103)
Both in Midwest	0.0793*	0.0795*	0.0803*	0.0801*
	(0.0194)	(0.0194)	(0.0195)	(0.0195)
Both in West	0.0094	0.0095	0.0100	0.0101
	(0.0167)	(0.0167)	(0.0167)	(0.0166)
Contiguous	0.0587	0.0587	0.0575	0.0591
	(0.0334)	(0.0335)	(0.0336)	(0.0336)
Constant	4.1630*	4.1617*	4.1695*	4.1697*
	(0.0148)	(0.0159)	(0.0106)	(0.0109)

The dependent variable is the log of the excess concordance between the two cities, all five models include city dummies, and all independent variables except for dummies are in logs. Statistical significance at the 5 percent level is indicated by “*”. Standard errors are White-corrected. Because of data availability, Austin, TX; Bethesda, MD; and Fort Lauderdale, FL are not included in this data set.

Table 4. Expected Excess Concordances from Model IV

Two cities in:	Expected Excess Concordance
1) different regions and states	64.2
2) the same state in the South, West, or Northeast	72.0
3) different Midwestern states	69.4
4) the same Midwestern state	77.9

Table 5. Estimated City Effects from Model IV

City	City Effect (est. coeff.)	Standard Error	City Effect (% points)
Phoenix-Mesa-Scottsdale AZ	0.1265	0.0099*	8.7
Atl-Sndy Sprgs-Martta GA	0.1106	0.0095*	7.5
Jacksonville FL	0.1018	0.0074*	6.9
Tampa-St Pete-Clearwater FL	0.0904	0.0095*	6.1
Charlotte-Gastonia-Concord NC-SC	0.0863	0.0116*	5.8
Orlando FL	0.0861	0.0093*	5.8
Las Vegas-Paradise NV	0.0830	0.0223*	5.6
Minneapolis-St Paul-Blmngtn MN-WI	0.0807	0.0109*	5.4
San Jose-Sunnyvale-Santa Clara, CA	0.0756	0.0120*	5.0
Milwkee-Wkesha-W Allis WI	0.0705	0.0117*	4.7
Memphis TN-AR-MS	0.0689	0.0149*	4.6
Fort Worth-Arlington, TX	0.0677	0.0093*	4.5
Bthsda-Frdrck-Gthrsbrg MD	0.0674	0.0105*	4.5
Richmond VA	0.0652	0.0079*	4.3
Houston-Baytown-Sugar Land, TX	0.0622	0.0109*	4.1
Philadelphia, PA	0.0602	0.0092*	4.0
Dllas-Plno-Irvng TX	0.0568	0.0101*	3.8
Miami-Miami Bch-Kendall, FL	0.0558	0.0097*	3.7
Pittsburgh PA	0.0558	0.0130*	3.7
Buffalo-Niagara Falls NY	0.0542	0.0079*	3.6
St Louis MO-IL	0.0504	0.0108*	3.3
Baltimore-Towson MD	0.0503	0.0096*	3.3
Portlnd-Vanc-Bvrtn OR-WA	0.0502	0.0127*	3.3
Chicgo-Nprvlle-Jliet IL	0.0411	0.0101*	2.7
NY-Wayne-White Plains, NY-NJ	0.0385	0.0096*	2.5
Rochester NY	0.0332	0.0089*	2.2
Boston-Cambridge-Quincy, MA	0.0330	0.0101*	2.2
Seattle-Bellevue-Everett, WA	0.0298	0.0138*	1.9
LA-Long Bch-Glndale, CA	0.0286	0.0113*	1.9
Cleveland-Elyria-Mentor OH	0.0209	0.0153	1.4
Indianapolis IN	0.0196	0.0101	1.3
Columbus OH	0.0078	0.0150	0.5
Nashvlle-Davidsn-Murfreesbro TN	0.0015	0.0121	0.1
Oklahoma City OK	-0.0026	0.0108	-0.2
Kansas City MO-KS	-0.0029	0.0141	-0.2
San Antonio TX	-0.0058	0.0160	-0.4
Louisville KY-IN	-0.0189	0.0162	-1.2
Ft Ldrdle-Pmpno Bch-Drfld Bch FL	-0.0338	0.0145*	-2.1
Snta Ana-Anahm-Irvine, CA	-0.0394	0.0154*	-2.5
Denver-Aurora, CO	-0.0403	0.0147*	-2.5
San Francsc-San Mateo-Redwd Cty, CA	-0.0406	0.0126*	-2.6
Salt Lake City UT	-0.0424	0.0141*	-2.7
Austin-Round Rock TX	-0.0440	0.0148*	-2.8
New Orlns-Metaire-Kennr LA	-0.0487	0.0118*	-3.1
Providence-Fall River-Warwick, RI-MA	-0.0510	0.0139*	-3.2
Oaklnd-Fremnt-Haywrd, CA	-0.0541	0.0177*	-3.4
Hrtfrd-W Hrtfrd-E Hrtfrd, CT	-0.0556	0.0230*	-3.5
Warren-Frmngtn Hills-Troy, MI	-0.0596	0.0174*	-3.7
Cincinnati-Middletn OH-KY-IN	-0.0733	0.0186*	-4.5
Dtroit-Lvnia-Drbrn MI	-0.0740	0.0161*	-4.6
San Diego-Carlsbd-San Marcos CA	-0.1066	0.0198*	-6.5
Virginia Beach-Norfolk-Nwprt Nws VA-NC	-0.1215	0.0181*	-7.3
Newark-Union, NJ-PA	-0.1270	0.0174*	-7.7
Wash-Arlington-Alexandria, DC-VA-MD	-0.1381	0.0202*	-8.3
Nassau-Suffolk, NY	-0.1709	0.0189*	-10.1
Edison, NJ	-0.1731	0.0162*	-10.2
Sacramento-Arden-Arcade-Roseville, CA	-0.1997	0.0240*	-11.6
Riverside-S Bernardno-Ontario CA	-0.2068	0.0239*	-12.0

Statistical significance at the 5 percent level is indicated by “*”.

Table 6. More Covariates of Concordance

	V	VI	VII	VIII
Industrial Similarity	-0.1205	-0.1859	-0.3429	-0.3691
	(0.4940)	(0.4961)	(0.5041)	(0.5048)
Industrial Diversity			1.9211*	1.9200*
			(0.9622)	(0.9631)
Same Principal State	0.1111*	0.1100*	0.1107*	0.1111*
	(0.0207)	(0.0210)	(0.0210)	(0.0211)
Same Secondary State	-0.0197	-0.0193	-0.0185	-0.0184
	(0.0291)	(0.0290)	(0.0292)	(0.0293)
Both in Northeast	0.0295	0.0309	0.0322	0.0316
	(0.0190)	(0.0185)	(0.0185)	(0.0184)
Both in South	-0.0108	-0.0093	-0.0086	-0.0087
	(0.0100)	(0.0100)	(0.0100)	(0.0100)
Both in Midwest	0.0748*	0.0702*	0.0711*	0.07149*
	(0.0191)	(0.0192)	(0.0193)	(0.0193)
Both in West	0.0077	0.0066	0.0071	0.0070
	(0.0171)	(0.0182)	(0.0182)	(0.0182)
Contiguous	0.0412	0.0402	0.0400	0.0397
	(0.0309)	(0.0310)	(0.0310)	(0.0309)
Racial Similarity	0.1006	0.0924	0.0786	0.0770
	(0.0930)	(0.0920)	(0.0917)	(0.0920)
High School Attainment	0.2225*	0.2099*	0.2092*	0.2036*
	(0.0695)	(0.0697)	(0.0697)	(0.0718)
Bachelor's Attainment	-0.1127	-0.1035	-0.0979	-0.0971
	(0.0744)	(0.0743)	(0.0745)	(0.0753)
Average Bank Size		0.9892	0.9834	0.9448
		(0.7097)	(0.7083)	(0.7092)
Banks per Establishments		-0.8560	-0.7183	-0.6983
		(1.8931)	(1.8934)	(1.8944)
Mean Establishment Size		1.2081*	1.1633*	1.1544*
		(0.5557)	(0.5584)	(0.5605)
City-Density				0.0289
				(0.0646)
City-Size				-1.9033
				(14.3430)
Constant	4.1727*	4.1862*	4.1917*	4.1921*
	(0.0150)	(0.0162)	(0.0161)	(0.0170)

The dependent variable is the log of the excess concordance between the two cities, all five models include city dummies, and all independent variables except for dummies are in logs. Statistical significance at the 5 percent level is indicated by "*". Standard errors are White-corrected.

Table 7. Expected Concordances from Model VII

Two cities in:	Different HS Attainment, Establishment Size, and Industrial Diversity	Same HS Attainment	Same Establishment Size	Same Industrial Diversity	Same HS Attainment, Establishment Size, and Industrial Diversity
1) different regions and states	63.8	64.7	64.5	64.4	66.1
2) the same state in the South, West, or Northeast	71.2	72.2	72.1	72.0	73.9
3) different Midwestern states	68.5	69.4	69.3	69.2	71.0
4) the same Midwestern state	76.5	77.5	77.4	77.3	79.3